LUND UNIVERSITY

Empirical Research on Information Transmission in the Hang Seng Index Markets: Evidence from Index Futures, Flagship Index and Finance Index

Master Programme in Finance

Master Essay I

May 2013

Supervisor

Lu Liu

Authors

Lang Qin

Yang Zhou

Acknowledgements

We would like to thank our supervisor Lu Liu at the Department of Economics in Lund University for her kind assistance and patience. We deeply appreciate her help.

Abstract:

This paper investigates the price discovery mechanism in the Hang Seng Index markets. The analysis is based on the cross-market volatility spillover effects by using the daily sets of Hang Seng Index (HSI), Hang Seng Finance Index (HSFIN), and Hang Seng Index futures (HSCIS00). In order to testify the influence of 2007 financial tsunami on the volatility spillover effect, the study employs the vector autoregressive model (VAR) and the bivariate GARCH model based on the BEKK parameterization. The testing period has been divided into the pre-crisis (1 April, 2003 to 31 July, 2007) and the crisis & recovery period (1 August, 2007 to 1 April, 2013). The empirical results depict that there exists bi-directional volatility spillover effect between HSI and HSCIS00 for the whole testing period. In contrast, a strong bi-directional volatility spillover effect between HSFIN and HSCIS00 is only recognized after the outbreak of the 2007 financial crisis.

Key words: Hang Seng Index Futures market, Volatility Spillovers, Financial Crisis, BEKK model

Table of content

1. Introduction

In this paper, we tend to explore how information is processed among the futures markets, the underlying index and the industry indexes. So and Tse (2004) argue that the examination of the volatility spillover effect is one of the three major approaches to the study of the price discovery of assets. Therefore, the analysis sheds light on the test of the volatility spillover effect to provide evidence on the price discovery mechanism in the Hong Kong market. Meanwhile, we aim to figure out the extent to which the futures shocks impinge upon the spot markets through which they are transmitted during the 2007 financial tsunami. In order to validate the test, we use daily data for the timeframe of April 1, 2003 to April 1, 2013 divided into two periods, before and after Aug 1, 2007.

Market efficiency hypothesis raised by Fama (1991) suggests that security prices fully convey all available information in spot and futures markets, which indicates both markets incorporate new information simultaneously (Zhong et al. (2003)). According to AY and Stengos (1998), this strong version of the hypothesis is on the premise of strictly following zero information and transaction costs. However, positive as they are in reality, this frictionless capital market theory is ill-founded. Tse (1999) finds new information is impounded more quickly in the futures markets than spot markets given institutional factors. Similarly, Silvapulle and Moosa (1999) point out spot prices react with a lag compared to futures prices. The causes mainly lie in futures market's lower transaction costs, higher liquidity, and flexibility of short selling (Cheung and Fung (1997); Bekiros and Diks (2008)), which suggest that futures prices may contain vital information on spot prices.

Extensive studies have been conducted in this area in the past decades. In normal conditions, the price-discovery process of the spot markets is affected closely by the futures markets (Lien and Tse (2002); Chan et al. (1991)), which indicates the use of futures prices as determination of spot market prices (Yang et al. (2012)). Zhong et al. (2003) present that regardless of the length of time, the prices of the spot and the futures markets are systematically attached. Garbade and Silber (1983) support the lead-lag relationship by examining seven commodity markets, conclude that futures markets lead spot markets, but the latter does not echo the former. So and Tse (2004) employ data from the Hang Seng Index and Hang Seng Index futures in the course of November 1999 and June 2002, suggesting that the futures markets dominate the spot markets in terms of information processing.

Existing empirical studies on information flows between spot and futures markets are typically centered on causality in the mean relationship. However, the relationship of conditional variances is given more weights in a growing body of research literature, with applications concerning information transmission mechanisms (Najand et al. (1992), Susmel and Engle (1994)). Ross (1989) establishes an arbitrage-free model, in which the rate of information transmission is primarily related to the volatility of price changes. Lin et al. (1994) also raise the topic of the predictability of volatility, and admit that the time-varying volatility is closely associated with information processing time.

Market interdependencies exist in terms of conditional second moments of the distribution of returns, which is known as volatility spillovers (So and Tse (2004)). Under financial integration, volatility in one market reacts to innovations in other markets (Gallo and Otranto (2008)). In order for price discovery process to proceed, the role of volatility is of importance, since variance is considered to be a source of information based on French and Roll (1986). Several other studies conclude that volatility in one market spills over to another market, especially when similar assets are considered (Hamao et al. (1990); Kawaller et al. (1990); Koutmos and Tucker (1996)).

The study by Tse (1999) employs the vector error correction model (VECM) and the bivariate EGARCH model to analyze the price discovery and volatility spillovers between the Dow Jones Industrial Average cash and futures markets. A conspicuous spillover effect of previous shock is found from futures market to underlying stock markets. Moreover, bad news is verified to have more power to aggravate the volatility than good news. Similar empirical conclusions are demonstrated by Patia and Rajib (2011). They investigate the relationship between the National Stock Exchange (NSE) S&P CNX Nifty futures and its underlying spot index dependent on returns and volatility. The VECM and Granger causality test are applied, and a unidirectional causality from futures to spot markets is recognized in this case. An investigation based on Korean stock markets (Kang et al. (2013)) shows that there exists a bi-directional relationship regarding volatility spillovers between spot and futures market. The bivariate GARCH model based on the BEKK parameterization is adopted as the methodology. There is also empirical evidence that spot prices lead futures prices. Moosa (1996) exhibits that spot price changes futures price among all kinds of market participants in a subsequent manner. Apart from those significant results, Dennis and Sim (1999) and Spyrou (2005) find no escalating effects of the futures trading on the spot market volatility.

The effect that volatility spillovers bring to financial markets has long been discussed. Edwards (1988) argues that futures market adds stability to spot market, since "it absorbs the brunt of the price adjustments"[1]. On the other hand, research conducted by Antoniou and Holmes (1995) state that futures trading engaged by institutional investors triggers excessive volatility on spot prices.

Empirical studies of financial markets meltdown attach an increasingly important role in volatility regimes. Diaw and Olivero (2011) investigate intraday dynamics of the CAC 40 index futures market and the underlying spot market under the 2007 financial distress. The EC-GARCH model presents the bi-directional relationship before the crisis and unidirectional volatility spillovers from spot to futures in the course of the crisis. Ding and Pu (2012) explore market linkage and information spillover across the U.S. stock, corporate bond, and credit derivatives markets in the pre-crisis, crisis, and recovery periods respectively. Their results suggest that during crisis, market linkage is stronger compared to the pre-crisis and recovery periods due to the increasing volatility and deteriorating funding liquidity.

In a long time, researches on the price discovery role of futures markets and possible

[1]Price discovery and volatility spillovers in index futures markets: Some evidence from Mexico. See Zhong, M., Darrat, A. F., & Otero, R. (2004).

volatility implications for the spot market generally focus on the U.S. market. Hong Kong has received relatively less attention regarding the Hang Seng Flagship Index, Hang Seng Finance Index and Hang Seng Index futures. As so, Hong Kong market becomes our interest. In addition, since Hong Kong has been a well-known developed market in the East-Asia, the extent of openness, the absence of foreign exchange controls and the high liquidity make it an ideal candidate for study. Moreover, volatility spillover effect under the recent financial crisis has been rarely discussed. Furthermore, the reason we choose Hang Seng Finance Index among the four industry indexes[2] as one of our examined market, is that the finance sector is recorded to be most seriously hit by the recent financial crisis. The collapse of the Lehman Brothers is one of the remarkable examples, resulting from the globally distributed collateral debt instruments (Onaran (2008)). Financial services, which account for 16% of the Hong Kong's GDP[3], are adversely affected (Zhang and Tong (2009)). Besides, Hong Kong stock market's significant downturn has led to a total market capitalization down 50 percent from 2007[4], wiping out more than HKD$6 trillion wealth[5]. Another discussion around spillovers of the U.S. subprime financial turmoil to Hong Kong is initiated by Zhang and Sun (2009). They argue that the significant volatility spillovers, together with past volatility shocks, exhibit persistent effect on future volatility in the Hong Kong financial market. The evidence implies that Hong Kong Finance Index may provide us with more significant results, compared to the other three industries, when measuring the effect of volatility spillover effects with respect to the 2007 financial crisis.

This paper distinguishes itself from the existing literature in at least two points. First of all, it intends to demonstrate whether there exists difference of volatility spillover effects between the spot and futures markets by introducing the recent global financial crisis. Previous studies either explore the pre-crisis market (Blanco et al.

---

[2] The four industries are Finance, Utilities, Properties, and Commerce & Industry respectively. Source: Hang Seng Indexes. Retrieved from http://www.hsi.com.hk/HSI-Net/HSI-Net

[3] Hong Kong's economy in the financial crisis. See Zhang and Tong (2009)

[4] HK stock market capitalization halved in 2008. Source: Xinhua net. Retrieved from http://www.china.org.cn/business/news/2009-03/04/content_17369955.htm

[5] Hong Kong's economy in the financial crisis. See Zhang and Tong (2009)

(2005); Longstaff et al. (2005)) or specifically focus on the crisis period (Longstaff (2010)). The distinct features across pre-crisis and crisis & recovery periods may provide a more comprehensive understanding of the information transmission mechanism in Hong Kong. In addition, we tend to examine the information transmission process between the industry index and futures market by bringing in the Hang Seng Finance Index. Intuitively, the three different markets are developed on almost the same underlying assets. Hang Seng Index futures (HSCIS00) is one of the derivative instruments of the underlying HSI, while the Hang Seng Finance Index (HSFIN) consists of 12 financial companies in the HSI. Those facts indicate that the three markets are affected by similar information. Hence, different information transmission abilities will to some extent reflect relative efficiencies in the information transmission process. This introduction enhances the understanding of the relationship between the futures and industry spot markets.

Some of the limitations exist in this paper. First of all, we did not find any authoritative literature to distinguish the crisis period from the recovery period. It may result in an over-estimation of the volatility spillover effect in the post-crisis period. Secondly, Granger causality test may provide spurious results regarding the time series estimation (Hutchison and Singh (1992)). Hiemstra and Jones (1993) find that the test power can be low in nonlinear causal relations. Therefore, the test results may not be totally reliable. Thirdly, VAR analysis itself, has constraints as well, for example, the lag length selection (Brooks (2008)), making it an imperfect instrument for estimation. Fourthly, Kroner and Ng (1998) point out that the standard BEKK model ignores the different asymmetric influence caused by positive or negative shock. In other words, the model in our paper cannot distinguish what type of the shock is.

The empirical results indicate highly significant bi-directional causalities between HSI and HSCIS00 during the whole testing period. Meanwhile, the percentage of movement in one market explained by the other is found to increase in all returns series. Furthermore, the estimation of the bivariate GARCH model suggests the existence of the bi-directional spillover effect between the return of HSI and

HSCIS00. However, the shocks spillover from the HSI to HSCIS00 is weak after the outburst of the financial crisis. It is noteworthy that both shock and volatility spillovers between the return of HSFIN and the return of HSCIS00 turn out to be considerably significant in both directions after Aug 2007.

The rest of this paper is organized as follows. The following part gives an overview of the Hong Kong stock market and preliminary data description. The third part explains the econometric methodology. The forth part discusses the empirical outcomes, and the final part draws the conclusions.

2. Data Description and Preliminary Analysis

2.1 Hong Kong stock market

The Hang Seng Index (HSI) was launched with 30 stocks on 24 November 1969， based on the performance of scale and liquidity. It expanded to 50 constitutional companies in 2007. Then, it has been classified into four industries, namely finance, utilities, properties and commerce & industry to give a clearer perspective on price movements on major sectors of the markets since 1985. One of these four indexes, Hang Seng Finance Index (HSFIN), consists of 12 financial companies among the HSI constituents. Hang Seng Index Futures (HSCIS00), one of the derivative instruments of HSI, was introduced by the Hong Kong Futures Exchange (HKFE) in May 1986. It has four contracts with different maturities (April, May, June, and Sep) every year. Each of these contracts writes the issuance month and the expiration month. When contracts expire in April, HKFE will issue a new contract that expires in December accordingly. The following table describes some of the details about the HSIF contracts.

The daily closing prices for HSI and HSFIN are obtained from Yahoo Finance and the DataStream respectively. The continuous daily settlement prices for the April contract of Hang Seng Index Futures are also supplied by the DataStream with the code “HSCIS00”. Though each of these contracts expires every eight months, the

"HSCIS00" shows the continuous prices by applying the buy-sell strategy before expiration of each contract.

Hang Seng Index Futures

Item	Contract Terms
Underlying Index	Hang Seng Index
HKATS Code	HIS
Contract Multiplier	HK$50 per index point
Minimum Fluctuation	One index point
Contract Months	Spot, next calendar month & next two calendar quarter months
Pre-Market Opening Period	8:45 am - 9:15 am & 12:30 pm - 1:00 pm
Trading Hours	9:15 am - 12:00 noon, 1:00 pm - 4:15 pm & 5:00 pm - 11:00 pm* (Expiring contract month closes at 4:00 pm on the Last Trading Day)
Last Trading Day	The Business Day immediately preceding the last Business Day of the Contract Month
Final Settlement Price	The average of quotations taken at (i) five (5) minute intervals from five (5) minutes after the start of, and up to five (5) minutes before the end of, the Continuous Trading Session of SEHK; and (ii) the close of trading on SEHK on the Last Trading Day.
Transaction Costs	Exchange Fee HK$10.00 Commission Levy HK$0.60 Commission Rate Negotiable

* After-hours futures trading session commence trading on 8 April 2013

Note: Hong Kong Exchange and Clearing Limited

In order to analyze the different information interaction between these markets in different time periods, we intend to apply the similar way as Suganthi and Bala (2004) do. They believe that the Asian financial crisis aggravate the variation in activity, so divide the data into three periods. In our case, we set the sample period from April 1, 2003 to April 1, 2013 and group them into two sub-periods as the financial tsunami breaks out in the middle. The data after Aug 2007 belongs to the group of crisis & recovery period, while the rest of it is marked as the pre-crisis period (Lewis P. C. (2010)).

2.2 Preliminary analysis

The fluctuations of figure 1 indicate that all of these price indexes are non-sationary from April 1 2003 to April 1 2013. Hence, we have to convert the original daily prices into daily logarithmic returns for all sample stock markets.

We calculate the continuously compounded daily returns (log returns) on these three time series as:

$$\mathrm{R}_{it} = \ln(\mathrm{P}_{\mathrm{it}}) - \ln\,(\mathrm{P}_{\mathrm{it-1}}) \quad (1)$$

The graphs in Figure 2 demonstrate the return series for these three markets, which are all stationary. Descriptive statistics of the return series are presented in Table 1. As can be seen, before the financial crisis, the observed volatilities of both the futures and spot market stay close, with the futures market a little bit higher. Then, the breakout of the financial crisis contributes significantly to the mean values' drop, further pushes the volatilities of both markets to a higher level.

In addition, negative skewness in the pre-crisis period is found to turn positive in the crisis & recovery period regarding all cases. The three return series are also observed to be more leptokurtic in the latter period, suggesting the non-normality of the data. The Jarque-Bera statistics further confirm the result with statistical significance, especially in the latter period. Thus, we reject the null hypothesis of normal distribution for the three returns series.

Then, the equilibrium relationship between the spot and futures price, denoted as the cost of carry model (Brooks (2008)), is presented as follows:

$$\mathrm{F}_{\mathrm{t}}^{*} = \mathrm{S}_{\mathrm{t}}\mathrm{e}^{(\mathrm{r-d})(\mathrm{T-t})} \quad (2)$$

where F_t^* indicates the fair futures price, S_t indicates the spot price, r represents the continuously compounded risk-free rate of interest, d represents the continuously compounded yield until the futures contract's maturity, and (T-t) shows the time to delivery of the futures contract.

By taking the logarithms of both sides, we have

$$f_t^* = s_t + (r - d)(T - t) \quad (3)$$

where f_t^* is the log of the fair futures price and s_t is the log of the spot price. Equation (3) shows a one-to-one relationship between the logs of the spot and futures prices in the long term. Thus, the first difference, which is the returns, should be stationary as the equilibrium price stays in the long term with the arbitrage opportunities promptly adjusted.

3. Methodology

3.1 Unit root test

In order to construct the model statistically adequate, we begin with both the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test based on daily returns of the three markets.

3.1.1 Dickey and Fuller (1979) define the test regression as follows:

$$\Delta x_t = \rho_0 + \rho x_{t-1} + \sum_{i=1}^{n} \delta_i \Delta x_{t-i} + \varepsilon_t \quad (4)$$

where x_t is the log price series, ρ_0 is a constant or drift, ρ equals to (α-1), Δ is the first difference operator, ε_t is a pure white noise error term, *i* (=1…n) is the number of lagged difference terms determined empirically to remove any autocorrelation in the error term ε_t, and Δx_{t-i} is the difference between x_{t-1} & x_{t-2}, x_{t-2} & x_{t-3}, etc. The null hypothesis is to test whether $\rho = 0$. Unit root exists when $\rho = 0$ $(\alpha = 1)$, meaning the tested time series is non-stationary. For stationarity, ρ should be negative.

3.1.2 KPSS considers a components representation of y, which includes the sum of a linear deterministic trend, a random walk, and a stationary error (Shin and Schmidt (1992)):

$$y_t = \varphi t + r_t + \varepsilon_t \quad (5)$$

where r_t depicts a random walk, $r_t \approx r_{t-1} + u_t$, u_t follows iid (0, σ_u^2). The initial value r_0 serves as a fixed intercept. The error term ε_t is stationary. The null of stationarity is simply $\sigma_u^2 = 0$.

The KPSS statistic for testing the null hypothesis can then be expressed as:

$$\hat{\eta}_t(l) = T^{-2} \sum_{t=1}^{T} \frac{S_t^2}{s^2(l)} \quad (6)$$

where $\hat{\eta}_t(l)$ implies that the statistic depends on the lag truncation parameter l, and $s^2(l)$ is a consistent estimator of σ^2.

3.2 VAR model

3.2.1 Granger-causality test

Granger-causality (GC) test identifies whether fluctuations a particular market has an impact on another market. The specific direction of causation flow is determined by the following two bivariate regressions,

$$x_t = \sum_{i=1}^{p} \alpha_i x_{t-i} + \sum_{i=1}^{p} \beta_i y_{t-i} + \varepsilon_t \quad (7)$$

$$y_t = \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{i=1}^{p} \beta_i x_{t-i} + \varepsilon_t \quad (8)$$

where x_t and y_t denote return series. x_t (y_t) presents a function of past values of itself, past and contemporaneous values of y_t (x_t).

In the VAR system, the standard F-test is used to examine Granger-causality between variables. If the lag coefficients of variable y in Eq. (7) are jointly zero, the null hypothesis is rejected by the F test. Under this occasion, we say that variable y Granger causes variable x. Similarly, if the lag coefficients of variable x in Eq. (8) are jointly zero, the null hypothesis is rejected by the F test. Then it can be said that the variable x Granger causes variable y.

3.2.2 Variance decomposition and impulse response function

After the examination of the Granger Causality, we apply the dynamic analysis, namely the variance decomposition and impulse response function. Variance decomposition develops a compact overview of the dynamic structures of a VAR Model. It measures the shock in the dependent variable itself, and also shocks to other variables in percentage (Brooks, 2008). The function of impulse response, on the other hand, is an alternative of variance decomposition, measuring how shocks affect future variables at a specific point in time within a dynamic system (Pesaran and Shin (1998)).

3.3 ARCH and bivariate GARCH models

Introduced by Engle (1982), time-variation in financial returns volatility is usually captured by ARCH and GARCH model. To determine whether ARCH effects are present in the residuals of an estimated model, LM test is performed in the first place. It tests the null hypothesis if the coefficient values of all q lags of the squared residual are not significantly different from zero. The null hypothesis is rejected with the test statistic value greater than the critical value from the χ^2 distribution. Only if ARCH effects exist can we proceed with further analysis with GARCH family models.

As we note, numerous variants and extensions of ARCH models have been proposed. A large body of literature has been devoted to univariate models (Bollerslev et al. (1994); Shephard (1996)). In examining volatility linkages among markets, a multivatiate GARCH approach is preferred over univariate settings to model co-movements (Saleem (2008)). So et al. (2003) also employ the multivariate GARCH (1, 1) model as their investigation of the volatility spillover process. In our paper, we use the extension of bivariate GARCH model that accommodates each market’s returns and the returns of other markets lagged one period, since we intend to compare two groups of the volatility spillover effect (HSI and HSCIS00 vs. HSFIN and HSCIS00). The model is stated as follows (Saleem (2009)):

$$r_t = \mu_t + \varepsilon_t \quad (9)$$

$$u_t|\Omega_{t-1} \sim N(0, H_t)$$

where r_t is an n×1 vector of daily returns at time t for each market. The n×1 vector of random errors μ_t represents the innovation for each market at time t with its corresponding n×n conditional variance-covariance matrix H_t. the information set Ω_{t-1} represents the market information available at time (t-1).

The own market mean spillovers and cross-market mean spillovers are measured by the estimates of matrix μ_t elements. This multivariate structure thus facilitates the measurement of the effects of innovations in the mean index returns on its own lagged returns and those of the lagged returns of futures markets.

The above model is based on the bivariate GARCH (1, 1) – BEKK representation (Engle and Kroner (1995)). The BEKK model ensures that the H matrix is always positive definite, which addresses the difficulty with early model proposal of Bollerslev et al. (1998) to impose specific restrictions on the conditional variance-covariance matrix.

Based on Brooks (2008), the H matrix can be presented as,

$$H_t = \Omega'\Omega + A'\varepsilon_{t-1}\varepsilon_{t-1}{}'A + B'H_{t-1}B \qquad (10)$$

where A, and B are 2×2 matrices of parameters and Ω represents an lower triangular matrix of parameters.

The formula can be expanded as follows.

$$\begin{vmatrix} h_{ss,t} & h_{sf,t} \\ h_{fs,t} & h_{ff,t} \end{vmatrix} = \begin{vmatrix} \Omega_{ss} & 0 \\ \Omega_{fs} & \Omega_{ff} \end{vmatrix}' \begin{vmatrix} \Omega_{ss} & 0 \\ \Omega_{fs} & \Omega_{ff} \end{vmatrix} + \begin{vmatrix} \beta_{ss,t} & \beta_{sf,t} \\ \beta_{fs,t} & \beta_{ff,t} \end{vmatrix}' \begin{vmatrix} h_{ss,t-1} & h_{sf,t-1} \\ h_{fs,t-1} & h_{ff,t-1} \end{vmatrix} \begin{vmatrix} \beta_{ss,t} & \beta_{sf,t} \\ \beta_{fs,t} & \beta_{ff,t} \end{vmatrix} + \begin{vmatrix} \alpha_{ss,t} & \alpha_{sf,t} \\ \alpha_{fs,t} & \alpha_{ff,t} \end{vmatrix}' \begin{vmatrix} \varepsilon_{ss,t-1}^2 & \varepsilon_{s,t-1}\varepsilon_{f,t-1} \\ \varepsilon_{s,t-1}\varepsilon_{f,t-1} & \varepsilon_{ff,t-1}^2 \end{vmatrix} \begin{vmatrix} \alpha_{ss,t} & \alpha_{sf,t} \\ \alpha_{fs,t} & \alpha_{ff,t} \end{vmatrix} \qquad (11)$$

$$h_{ss,t} = \Omega_{ss}^2 + \Omega_{fs}^2 + \alpha_{ss,t}^2\varepsilon_{ss,t-1}^2 + 2\alpha_{fs,t}\alpha_{ss,t}\varepsilon_{s,t-1}\varepsilon_{f,t-1} + \alpha_{fs,t}^2\varepsilon_{ff,t-1}^2 + \beta_{ss,t}^2 h_{ss,t-1} + 2\beta_{ss,t}\beta_{fs,t}h_{fs,t-1} + \beta_{fs,t}^2 h_{ff,t-1} \qquad (12)$$

$$h_{ff,t} = \Omega_{ff}^2 + \alpha_{sf,t}^2\varepsilon_{ss,t-1}^2 + 2\alpha_{sf,t}\alpha_{ff,t}\varepsilon_{s,t-1}\varepsilon_{f,t-1} + \alpha_{ff,t}^2\varepsilon_{ff,t-1}^2 + \beta_{sf,t}^2 h_{ss,t-1} + 2\beta_{sf,t}\beta_{ff,t}h_{fs,t-1} + \beta_{ff,t}^2 h_{ff,t-1} \qquad (13)$$

$$h_{sf,t} = h_{fs,t} = \Omega_{fs}\Omega_{ff} + \alpha_{ss,t}\alpha_{sf,t}\varepsilon_{ss,t-1}^2 + (\alpha_{ss,t}\alpha_{ff,t} + \alpha_{ff,t}\alpha_{fs,t})\varepsilon_{s,t-1}\varepsilon_{f,t-1} + \alpha_{ff,t}\alpha_{fs,t}\varepsilon_{ff,t-1}^2 + \beta_{ss,t}\beta_{sf,t}h_{ss,t-1} + (\beta_{fs,t}\beta_{ff,t} + \beta_{sf,t}\beta_{fs,t})h_{sf,t-1} + \beta_{ff,t}\beta_{fs,t}h_{ff,t-1} \qquad (14)$$

where H_t (a 2×2 matrix) expresses the conditional variance-covariance. Ω denotes the intercept coefficient in a 2×2 lower triangular matrix with three parameters. A (a 2×2 matrix) estimates to what degrees the current conditional variances are affected by the past shocks or news. B (a 2×2 matrix) estimates to what degrees the current conditional variances are influenced by the past conditional variances. The diagonal parameters of A and B indicate the effects of own market, namely ARCH and GARCH effects respectively. Meanwhile, the off-diagonal parameters of the two matrices indicate the shocks spillover effects and volatility spillover effects are transmitted across the spot and future market respectively.

In order to examine the volatility spillover effects across markets, the null hypothesis of the bivariate GARCH is presented as follows.

$$H_0: \alpha_{sf,t} = \alpha_{fs,t} = \beta_{sf,t} = \beta_{fs,t} = 0$$

If the results reject the null hypothesis of no volatility spillover effects, we can generate the extent of shock spillovers and volatility spillovers between the spot and futures markets.

With the conditional normality assumption, the parameters of the above model can be estimated by maximizing the following log-likelihood function,

$$\ell(\theta) = -\frac{TN}{2}\log 2\pi - \frac{1}{2}\sum_{t=1}^{T}(\log|H_t| + \varepsilon_t' H_t^{-1} \varepsilon_t) \quad (15)$$

where θ denotes all the parameters unknown, N is the number of assets and T is the number of observations.

4. Empirical Analysis

4.1 Unit root test

Results generated by the ADF and KPSS tests allow us to reject the null hypothesis of the unit root in favor of alternate hypothesis of stationarity (even at 1% critical value), with p-values highly significant. Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test is also applied here. With insignificant results (at 5% critical value), the null hypothesis of stationarity cannot be rejected. Thus, both tests present the same results (Table 2).

Since the three return series are proved to be stationary, we can proceed to the establishment of the vector autoregressive model (VAR).

4.2 VAR model

4.2.1 Lag order selection

The VAR lag order selection results are shown in Table 3. The optimal lag length (k) in the VAR model is selected by the AIC or the SIC. Before the financial crisis, the lag length of 5 is chosen between the return of HSI and HSCIS00. During the same period, the return of HSFIN and HSCIS00 select the optimal lag length to be 1. After the crisis, it can be seen that the optimal lag length changes to 8 between the return of HSI and HSCIS00. Meanwhile, the lag length turns 6 regarding the return of HSFIN and HSCIS00. Those lag length selections lay the foundation for the Granger Causality test performed later. Once it is estimated, we then employ the other two dynamic analyses: variance decomposition (VDC) and impulse response function (IRF).

4.2.2 Granger-causality test

Table 4 presents the causality test results obtained by VAR estimation using Eqs. (7) and Eqs. (8). Before the financial crisis of Aug 2007, the VAR estimates between the return of HSCIS00 and the return of HSI show the significant p-values at the 5% level. Therefore, we can say that the return of HSCIS00 Granger causes the return of HSI. Similarly, the return of HSI Granger causes the return of HSCIS00. There is also causality from the return of HSCIS00 to the return of HSFIN at the 10% level in the same period. However, insignificant causality works in the opposite direction. During and after the financial crisis of Aug 2007, highly significant bi-directional Granger causality is found between the return of HSCIS00 and the return of HSI. Moreover, causality from the return of HSCIS00 to the return of HSFIN also turns highly significant in the period. At the same time, there exists much weaker causality from the return of HSFIN to the return of HSCIS00. Here, the results may be interpreted as suggesting information is incorporated more quickly in the HSI-HSCIS00 relation than in the HSFIN & HSCIS00 relation regarding the whole testing period. In addition, information regarding the return of HSI has better ability to explain the return of HSCIS00, than that of the return of HSFIN to explain the return of HSCIS00.

4.2.3 Variance decomposition and impulse response function

In the panel A and B of table 5, the shock of return on HSI interpret its own movement in an overwhelming proportion, while the shock of return of HSCIS00 increases the ability to explain the movement in HSI in the latter time period. In addition, the return's shock on HSI can explain the movement in the return of HSCIS00 in a relatively large percentage, especially after the financial crisis. In the rest panels of this table, similar trend is depicted between the returns of HSFIN and HSCIS00. In detail, the movement of HSFIN is illustrated by the own shock diminishes a little after the financial crisis. The return of HSCIS00, which is influenced by the shock of the HSFIN return, increases sharply, about 20 percent during the crisis & recovery period. Here, the results controvert what we have obtained in the Granger causality test. According to Brooks (2008), the Cholesky ordering has a significant impact on the results of the variance decomposition. In other words, different ordering may lead to very different results. However, with rearranging different orders, there still exist controversial results with the test of the Granger causality. The latter test has its limitations as well, as discussed in previous part.

Meanwhile, the impulse response showed in figure 3 also indicates the similar trends as the variance decomposition between the spot and futures markets. The response from one market to the other is more lasting and more fluctuant for both modeled groups after the breakout of the financial crisis.

4.3 ARCH and bivariate GARCH models

4.3.1 LM test

LM test shows significant results across the three return series in table 6. Therefore, we reject the null hypothesis of no ARCH effects.

4.3.2 BEKK-GARCH

Table 7 represents the empirical results on the basis of the BEKK (1, 1) model. The diagonal variables of matrix A (i.e.$\alpha_{ss,t}$, $\alpha_{ff,t}$) that capture the volatility effects caused by its own past shocks are noticeably significant, except for the case between the return of HSFIN and HSCIS00 before the financial crisis. Compare the two periods, the ARCH effects for own market changes are more visible in the group of HSFIN and HSCIS00. On the other hand, the diagonal variables of matrix B (i.e.$\beta_{ss,t}$ $\beta_{ff,t}$) that capture the volatility effects caused by its own past volatility are also considerably significant, except for the case between the return of HSI and HSCIS00 during the crisis & recovery period. It is noteworthy that these coefficients imply a positive relation between the own lagged conditional variance and the current conditional variance in three markets in the whole testing period.

The parameters in the off-diagonal of matrix A (i.e.$\alpha_{sf,t}$ $\alpha_{fs,t}$) describe the shock spillovers effect across markets. At the same time, the cross-market volatility spillovers effect can be interpreted by the off-diagonal parameters of matrix B (i.e.$\beta_{sf,t}$ $\beta_{ss,t}$). Before the financial crisis, there is bi-directional cross-effect of shock spillovers between the return of HSI and HSCIS00, namely a positive reaction to the future conditional variance from the lagged error of the spot market and a negative reaction in the opposite direction. After Aug 2007, only the past futures shock has spillover effects to the spot market between the return of HSI and HSCIS00. During the whole period, there exist strong bi-directional cross-effects of volatility spillovers between the return of HSI and HSCIS00. In detail, regarding the two directions, the lagged spot conditional variance to the current futures variance has a bit bigger volatility spillovers effect in the whole period.

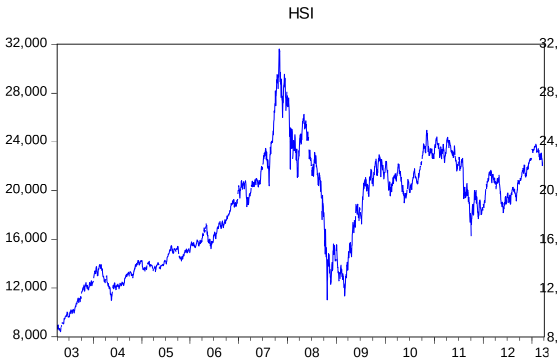
In the meantime, there is weak evidence indicating the shock spillovers and volatility spillovers between the return of HSFIN and HSCIS00 before the financial crisis, as all four off-diagonal parameters are insignificant. However, it is remarkable that all statistical results indicate the cross-market effects between the return of HSFIN and HSCIS00 in the crisis & recovery time period. To be specific, positive shock spillovers, provided by the lagged spot error, are indicated on futures conditional variance. The other off-diagonal parameter of matrix A, measuring the shock spillovers in the contrary direction, indicates a negative relation. Similarly, negative volatility spillover effect to futures conditional variance is represented by the lagged spot conditional variance, whereas a negative result is provided in the other direction. In addition, all off-diagonal elements in the group of HSFIN and HSCIS00 show highly significant cross-market spillover effects as the group of HSI and HSCIS00.

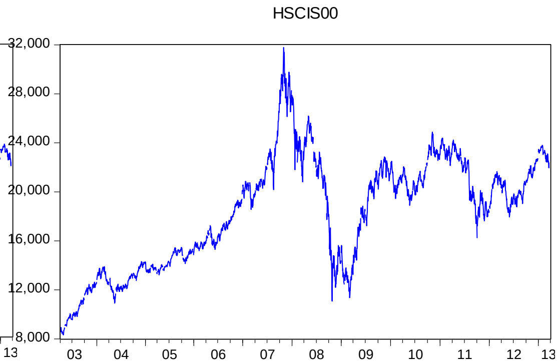
5. Conclusion

This paper examines the price discovery process among the Hong Kong Hang Seng Index markets. Significant co-movements are recognized among the returns of HSI, HSFIN and HSCIS00. The results from the bivariate GARCH model based on the BEKK parameterization provide stark evidence that, the volatilities of the spot and futures market spill over to each other. However, we see stronger volatility spillover effect from the futures to the spot in general. In the whole testing period, bi-directional volatility spillover effects are present in the modeled pair of HSI return and HSCIS00 return. In contrast, the shock and volatility spillovers between the other pair, which is the HSFIN return and HSCIS00 return, only become significant in the crisis & recovery period. All in all, we find a stronger tie in the two testing pairs during and after the introduction of the 2007 financial crisis. This to some extent confirms our hypothesis in the first place. The result is also in line with previous well-documented observations regarding the impact brought from financial markets meltdown. The stronger signaling effect from the futures to spot corroborates the trading cost hypothesis as well. The least cost instrument is found to lead others in the price discovery mechanism (So and Tse (2004)). In this case, since HSI constitutes over 60% of capitalization of the Hong Kong Stock Exchange[6], the tracking costs of the index futures is less costly than individual stocks in the spot market. Hence, futures market plays a more important role in the price discovery process in the Hong Kong market.

[6]Source: Hang Seng Indexes. Retrieved from: http://www.hsi.com.hk/HSI-Net/HSI-Net

Appendix:





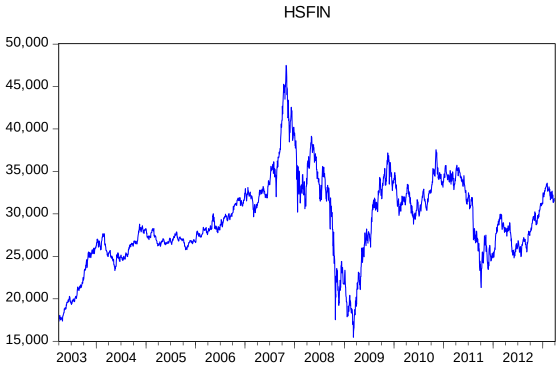


Figure 1: Daily price indices for the spot and futures markets during the whole test period.

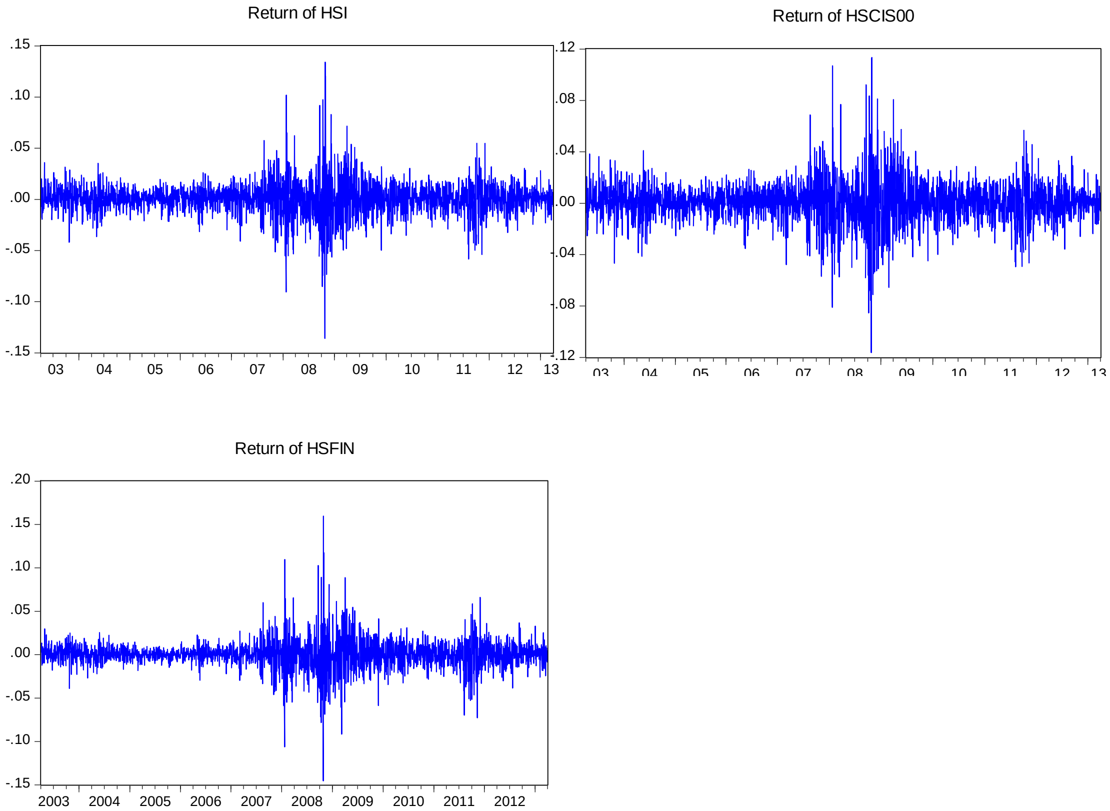


Figure 2: Daily return price indices for the spot and futures markets during the whole test period.

Table 1: Descriptive statistics for the returns

	Return of HSI		Return of HKHSFIN		Return of HSCIS00	
Sample	4/02/2003 — 7/31/2007	8/02/2007 — 4/01/2013	4/02/2003 — 7/31/2007	8/02/2007 — 4/01/2013	4/02/2003 — 7/31/2007	8/02/2007 — 4/01/2013
Observations	1078	1428	1078	1428	1078	1428
Mean	0.000920	-4.87e-06	0.000651	-7.49e-05	0.000926	5.02e-07
Median	0.000824	0.000000	0.000133	0.000000	0.000912	0.000000
Maximum	0.035998	0.134068	0.030111	0.159744	0.040957	0.113402
Minimum	-0.041836	-0.135820	-0.039060	-0.145385	-0.047763	-0.116308
Std. Dev.	0.009576	0.019437	0.007385	0.020322	0.010714	0.019735
Skewness	-0.250448	0.095737	-0.067858	0.109261	-0.278722	0.090603
Kurtosis	4.485243	9.713891	5.307312	11.12094	4.557357	7.983674
Jarque-Bera	110.3533	2684.224	251.5243	4064.448	122.8968	1479.756
P-Value	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

Table 2: Stationary Test

	Return of HSI		Return of HSFIN		Return of HSCIS00	
Test	4/02/2003-7/31/2007	8/02/2007-4/01/2013	4/02/2003-7/31/2007	8/02/2007-4/01/2013	4/02/2003-7/31/2007	8/02/2007-4/01/2013
ADF	-31.47793 (0.0000)	-39.40075 (0.0000)	-32.51746 (0.0000)	-40.17722 (0.0000)	-33.51627 (0.0000)	-38.97654 (0.0000)
KPSS	0.106151	0.076551	0.263170	0.070293	0.102063	0.074550

Note that: the critical value for the ADF test is -3.436205 at 1% confidence level and -2.864013 at 5% confidence level. The asymptotic critical values for the KPSS test is 0.739000 at 1% confidence level and 0.463000 at 5% confidence level.

Table 3: VAR Lag Order Selection Criteria

Endogenous variables: Return of HSI & Return of HSCIS00					
Sample	4/02/2003—7/31/2007			Included observations: 1070	
Lag	LR	FPE	AIC	SC	HQ
2	74.39191	6.10e-10	-15.54142	-15.49492*	-15.52381
3	26.55543	6.00e-10	-15.55893	-15.49383	-15.53427*
5	12.29807*	5.98e-10*	-15.56233*	-15.46003	-15.52358
Sample	8/02/2007—4/01/2013			Included observations: 1420	
Lag	LR	FPE	AIC	SC	HQ
4	47.51287	6.81e-09	-13.12930	-13.06264*	-13.10440
8	20.64581*	6.60e-09*	-13.16019*	-13.03428	-13.11315*
Endogenous variables: Return of HSFIN & Return of HSCIS00					
Sample	4/02/2003—7/31/2007			Included observations: 1122	
Lag	LR	FPE	AIC	SC	HQ
0	NA	1.81e-09	-14.45564	-14.44669*	-14.45226
1	19.46821*	1.79e-09*	-14.46591*	-14.43905	-14.45576*
Sample	8/02/2007—4/01/2013			Included observations: 1470	
Lag	LR	FPE	AIC	SC	HQ
1	88.51421	1.75e-08	-12.18487	-12.16327*	-12.17681
2	20.37827	1.74e-08	-12.19334	-12.15733	-12.17991*
6	10.01028*	1.72e-08*	-12.20068*	-12.10706	-12.16577

* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

Table 4: Granger Causality Test

Return of HSI & Return of HSCIS00				
Dependent variable / Excluded	Return of HSI		Return of HSCIS00	
	4/02/2003-7/31/2007 (df.=5)	8/02/2007-4/01/2013 (df.=8)	4/02/2003-7/31/2007 (df.=5)	8/02/2007-4/01/2013 (df.=8)
Return of HSI	--	--	0.0349**	0.0346**
Return of HSCIS00	0.0277**	0.0000***	--	--
Return of HSFIN & Return of HSCIS00				
Dependent variable / Excluded	Return of HSFIN		Return of HSCIS00	
	4/02/2003-7/31/2007 (df.=1)	8/02/2007-4/01/2013 (df.=6)	4/02/2003-7/31/2007 (df.=1)	8/02/2007-4/01/2013 (df.=6)
Return of HSFIN	--	--	0.5037	0.6030
Return of HSCIS00	0.0652*	0.0067***	--	--

Note that *** means there is Granger causality at 1% confident level, ** means there is Granger causality at 5% confident level, * means there is Granger causality at 10% confident level.

Table 5: Variance Decomposition Examinations

Variance Decomposition of Return of HSI (HSI & HSCIS00)						
Panel:A	4/02/2003—7/31/2007			8/02/2007—4/01/2013		
Period	S.E.	Return of HSI	Return of HSCIS00	S.E.	Return of HSI	Return of HSCIS00
1	0.009516	100.0000	0.000000	0.019069	100.0000	0.000000
5	0.009582	98.90727	1.092727	0.019443	96.67235	3.327650
10	0.009588	98.81545	1.184547	0.019554	95.99055	4.009453
15	0.009588	98.81465	1.185345	0.019557	95.97422	4.025781
20	0.009588	98.81465	1.185349	0.019558	95.97273	4.027271
25	0.009588	98.81465	1.185349	0.019558	95.97237	4.027633
Variance Decomposition of Return of HSCIS00 (HSI & HSCIS00)						
Panel:B	4/02/2003—7/31/2007			8/02/2007—4/01/2013		
Period	S.E.	Return of HSI	Return of HSCIS00	S.E.	Return of HSI	Return of HSCIS00
1	0.010660	94.30818	5.691818	0.019660	95.41348	4.586519
5	0.010725	93.40355	6.596449	0.019735	95.11778	4.882225
10	0.010740	93.22243	6.777571	0.019844	94.54072	5.459280
15	0.010740	93.22126	6.778737	0.019846	94.53526	5.464744
20	0.010740	93.22125	6.778750	0.019848	94.53339	5.466609
25	0.010740	93.22125	6.778750	0.019848	94.53313	5.466868
Cholesky Ordering: Return of HSI Return of HSCIS00						

Table 5: Variance Decomposition Examinations

Variance Decomposition of Return of HSFIN (HSFIN & HSCIS00)

Panel:C	4/02/2003—7/31/2007			8/02/2007—4/01/2013		
Period	S.E.	Return of HSFIN	Return of HSCIS00	S.E.	Return of HSFIN	Return of HSCIS00
1	0.007375	100.0000	0.000000	0.020251	100.0000	0.000000
5	0.007395	99.70132	0.298683	0.020402	98.93501	1.064992
10	0.007395	99.70132	0.298683	0.020421	98.81556	1.184435
15	0.007395	99.70132	0.298683	0.020421	98.81384	1.186163
20	0.007395	99.70132	0.298683	0.020421	98.81381	1.186194
25	0.007395	99.70132	0.298683	0.020421	98.81381	1.186195

Variance Decomposition of Return of HSCIS00 (HSFIN & HSCIS00)

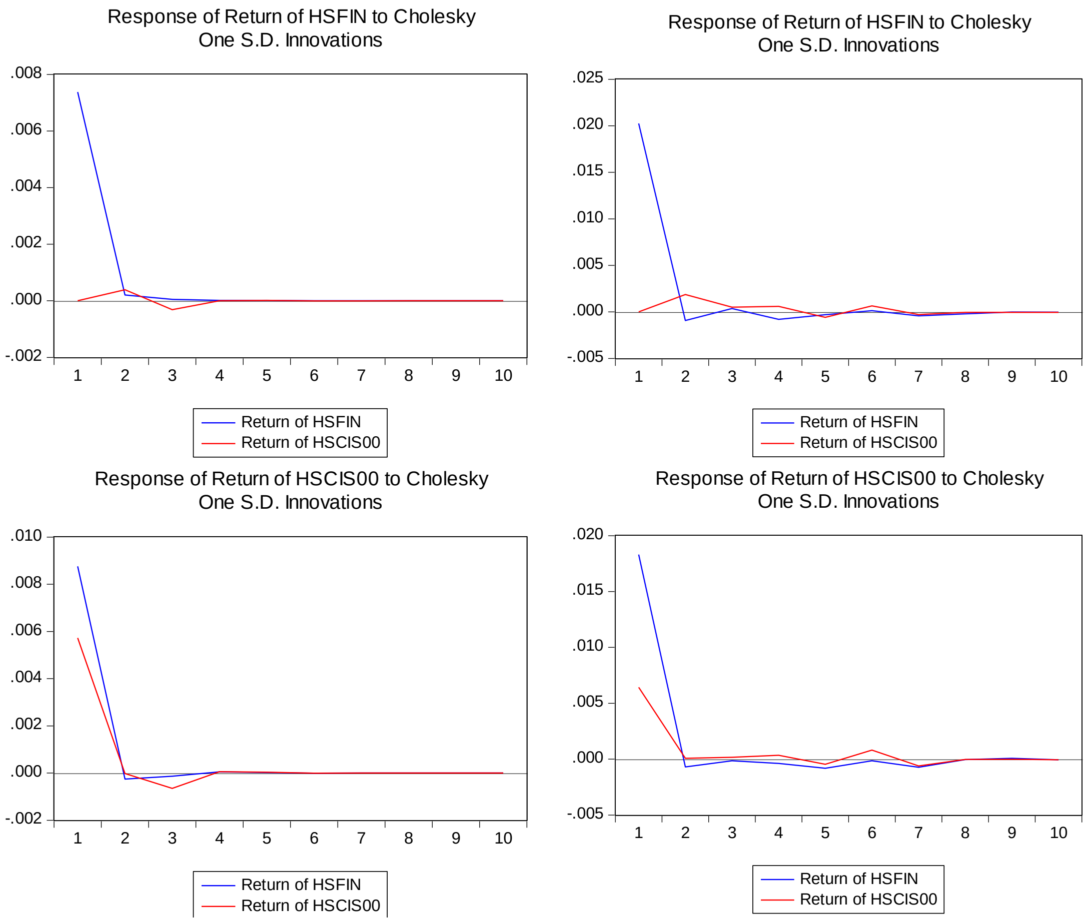
Panel:D	4/02/2003—7/31/2007			8/02/2007—4/01/2013		
Period	S.E.	Return of HSFIN	Return of HSCIS00	S.E.	Return of HSFIN	Return of HSCIS00
1	0.010462	69.96609	30.03391	0.019406	89.02738	10.97262
5	0.010487	69.99101	30.00899	0.019449	88.97921	11.02079
10	0.010487	69.99101	30.00899	0.019490	88.75507	11.24493
15	0.010487	69.99101	30.00899	0.019491	88.75215	11.24785
20	0.010487	69.99101	30.00899	0.019491	88.75210	11.24790
25	0.010487	69.99101	30.00899	0.019491	88.75210	11.24790

Cholesky Ordering: Return of HSFIN Return of HSCIS00

Return of HSI & Return of HSCIS00

(4/02/2003—7/31/2007) (8/02/2007—4/01/2013)

Figure 3: Impulse Response Examinations



Return of HSFIN & Return of HSCIS00

(4/02/2003—7/31/2007) (8/02/2007—4/01/2013)

Figure 3: Impulse Response Examinations

Table 6: LM Test

	Return of HSI		Return of HSFIN		Return of HSCIS00	
	4/02/2003 — 7/31/2007	8/02/2007 — 4/01/2013	4/02/2003 — 7/31/2007	8/02/2007 — 4/01/2013	4/02/2003 — 7/31/2007	8/02/2007 — 4/01/2013
F-statistic	8.293138	142.3770	6.297926	135.2640	5.674313	139.8687
Critical Value	3.1071	3.1421	3.1123	3.1471	3.1071	3.1421
P-Value	0.0000	0.0000	0.0003	0.0000	0.0007	0.0000

Table 7: Estimated Bivariate GARCH (1, 1)

	HSI & HSCIS00				HSFIN & HSCIS00			
	4/02/2003—7/31/2007		8/02/2007—4/01/2013		4/02/2003—7/31/2007		8/02/2007—4/01/2013	
	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value
μ_1	0.000842	0.0039	0.000552	0.2051	0.00034	0.1038	4.74E-05	0.8992
μ_2	0.000809	0.0103	0.000547	0.2280	0.000575	0.0546	7.63E-05	0.8279
Ω_{ss}	-0.001235	0.0013	2.16E-07	1.0000	5.68E-07	1.0000	-0.00045	0.0001
Ω_{fs}	0.000345	0.4439	0.014405	0.0000	0.000218	0.8398	0.001595	0.0000
Ω_{ff}	0.001879	0.0026	0.015449	0.0000	-0.003695	0.0083	0.001375	0.0000
$\alpha_{ss,t}$	0.395952***	0.0000	-0.169676***	0.0080	0.23925***	0.0018	0.55055***	0.0000
$\alpha_{ff,t}$	-0.66674***	0.0000	-0.376189***	0.0000	0.078179	0.2448	-0.482795***	0.0000
$\beta_{ss,t}$	0.824845***	0.0000	0.662588***	0.0000	0.883376***	0.0000	0.838097***	0.0000
$\beta_{ff,t}$	0.654965***	0.0000	-0.033189	0.8299	0.78917***	0.0000	1.089205***	0.0000
$\alpha_{sf,t}$	0.8004***	0.0000	-0.075806	0.2512	0.025626	0.8487	0.581461***	0.0000
$\alpha_{fs,t}$	-0.217999***	0.0059	-0.30281***	0.0000	-0.009193	0.8083	-0.352999***	0.0000
$\beta_{sf,t}$	0.355593***	0.0004	-0.337733**	0.0308	0.231542	0.2724	-0.12237***	0.0000
$\beta_{fs,t}$	0.139666***	0.0000	-0.960594***	0.0000	0.075781	0.4918	0.135735***	0.0000

Note that *** means significance at 1% confidence level, **means significance at 5% confidence level

Bibliography:

Antoniou, A., & Holmes, P. (1995). Futures trading, information and spot price volatility: evidence for the FTSE-100 stock index futures contract using GARCH. *Journal of Banking & Finance*, 19(1), 117-129.

AY, R. G., & Stengos, T. (1998). Moving average rules, volume and the predictability of security returns with feed forward networks. *Journal of Forecast*, 17, 401-414.

Bekiros, S. D., & Diks, C. G. (2008). The relationship between crude oil spot and futures prices: Cointegration, linear and nonlinear causality. *Energy Economics*, 30(5), 2673-2685.

Blanco, R., Brennan, S., & Marsh, I. W. (2005). An empirical analysis of the dynamic relationship between investment-grade bonds and credit default swaps. *Journal of Finance,* 60, 2255–2281.

Bollerslev, T., Engle, R. F., & Wooldridge, J. M. (1988). A capital asset pricing model with time-varying covariances. *The Journal of Political Economy*, 116-131.

Bollerslev, T., Engle, R. F., & Nelson D. (1994). ARCH models, in R. F. Engle and D. L. McFadden (eds.). *Handbook of Econometrics*, Vol. IV, Elsevier Science B.V.

Brooks, C. (2008). Introductory Econometrics for Finance. 2nd Edition, *Cambridge University Press,* 300-301, 343-344, 432-435.

Chan, K., Chan, K. C., & Karolyi, G. A. (1991). Intraday volatility in the stock index and stock index futures markets. *Review of Financial Studies,* 4(4), 657-684.

Cheung Y. W. & Fung H. G. (1997). Information flows between Eurodollar spot and futures markets. *Multinational Finance Journal*, Vol. 1, No. 4, 255-271.

Dennis, S. A., & Sim, A. B. (1999). Share price volatility with the introduction of individual share futures on the Sydney Futures Exchange. *International Review of Financial Analysis*, 8(2), 153-163.

Diaw, A. B., & Olivero, B. (2011). Empirical evidence of CAC 40 futures volatility under crisis. *International Research Journal of Finance & Economics*, Issue 67, 130-141.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, 74(366a), 427-431.

Ding, L. & Pu, X. L. (2012). Market linkage and information spillover: evidence from pre-crisis, crisis and recovery periods. *Journal of Economics and Business*, Vol. 64, Issue 2, 145-159.

Edwards, F. R. (1988). Does futures trading increase stock market volatility?. *Financial Analysts Journal*, 63-69.

Engle, R. F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of U.K. inflation. *Econometrica 50*, 987-1008.

Engle, R. & Kroner, K. F. (1995). Multivariate simultaneous generalized ARCH. *Econometric Theory*, 11, 122-150.

Fama, E. F. (1991). Efficient capital markets: II. *the Journal o Finance*, Vol. XLVI, No. 6.

French, K. R. & Roll, R. (1986). Stock return variances: The arrival of information and the reaction of traders. *Journal of Financial Economics*, 17, 5-26.

Garbade, K. D., & Silber, W. L. (1983). Price movements and price discovery in futures and cash markets. *The Review of Economics and Statistics*, 65(2), 289-297.

Gallo, G. M., & Otranto, E. (2008). Volatility spillovers, interdependence and comovements: A Markov Switching approach. *Computational Statistics & Data Analysis*, 52(6), 3011-3026.

Hamao, Y., Masulis, R. W., & Ng, V. (1990). Correlations in price changes and volatility across international stock markets. *Review of Financial studies*, 3(2), 281-307.

Hiemstra, C. (1992). Detection and description of linear and nonlinear dependence in daily Dow Jones stock returns and NYSE trading volume. Working paper. *University of Strathclyde and Securities and Exchange Commission.*

Hutchison, M., & Singh, N. (1992). Exports, non-exports and externalities: a Granger causality approach. *International Economic Journal*, 6:2, 79-94

Karmakar, M. (2010). Information transmission between small and large stocks in the National Stock Exchange in India: An empirical study. *The Quarterly Review* *of Economics and Finance*, 50(1), 110-120.

Kang, S. H., Cheong, C. & Yoon, S. M. (2013). Intraday volatility spillovers between spot and futures indices: Evidence from the Korean stock market. *Physical A*, 1795–1802.

Kawaller, I. G., Koch, P. D., & Koch, T. W. (1990) Intraday relationships between volatility in S&P 500 futures prices and volatility in the S&P 500 index. *Journal of Banking and Finance*, 14, 373-397.

Koutmos, G., & Tucker, M. (1996). Temporal relationships and dynamic interactions between spot and futures stock markets. *Journal of Futures Markets*, 16(1), 55-69.

Lewis, P. C. (2010). The global financial crisis 2007–8: origins, nature and consequences. *Global Security in Encyclopedia of Life Support Systems (EOLSS).*

Lien, D., & Tse, Y. K. (2002). Some recent developments in futures hedging. *Journal of Economic Surveys*, 16(3), 357-396.

Lin, W. L., Engle, R. F., & Ito, T. (1994). Do bulls and bears move across borders? International transmission of stock returns and volatility. *Review of Financial Studies*, 7, 507-538.

Longstaff, F. A., Mithal, S., & Neis, E. (2005). Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market. *The Journal of Finance*, 60, 2213–2253.

Longstaff, F.A. (2010).The subprime credit crisis and contagion in financial markets. *Journal of Financial Economics*, 97, 436–450.

Moosa, I. A. (1996). An econometric model of price determination in the crude oil futures markets. In *Proceedings of the Econometric Society Australasian meeting*,Vol. 3, 373-402.

Najand, M., Rahman, H., & Yung, K. (1992). Inter-currency transmission of volatility in foreign exchange futures. *Journal of Futures Markets*, Vol.12, Issue 6, 609-620.

Onaran, Y. (2008). Subprime losses top $379 billion on balance-sheet marks: table. *Bloomberg. com*.

Patia, P. C. & Rajib, P. (2011). Intraday return dynamics and volatility spillovers between NSE S&P CNX Nifty stock index and stock index futures. *Applied Economics Letters*, 567–574.

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics letters*, 58(1), 17-29.

Ross, S. (1989). Information and volatility: the no-arbitrage martingale approach to timing and resolution irrelevancy. *Journal of Finance*, 44, 1-17.

Saleem, K. (2009). International linkage of the Russian market and the Russian financial crisis: A multivariate GARCH analysis. *Research in International Business and Finance*, 23(3), 243-256.

Saleem, K., and Vaihekoski, M. (2008). Pricing of global and local sources of risk in Russian stock market. *Emerging Markets Review*, Vol.9, Issue 1, 40-56.

Shephard, N. (1996). Statistical aspects of ARCH and stochastic volatility. *Monographs on Statistics and Applied Probability*, 65, 1-68.

Shin, Y., & Schmidt, P. (1992). The KPSS stationarity test as a unit root test. *Economics Letters*, 38(4), 387-392.

Silvapulle, P., & Moosa, I. A. (1999). The relationship between spot and futures prices: evidence from the crude oil market. *Journal of Futures Markets*, 19(2), 175-193.

So, R. D. & Tse, Y. M. (2004). Price discovery in the Hang Seng markets: index, futures and the Tracker fund. *The Journal of Futures Markets*, 887–907.

Spyrou, S. I. (2005). Index futures trading and spot price volatility evidence from an emerging market. *Journal of Emerging Market Finance*, 4(2), 151-167.

Susmel R., & Engle R. F. (1994). Hourly volatility spillovers between international equity markets, *Journal of International Money and Finance,* Vol. 13, Issue 1, 3-25.

Suganthi, R. & Bala, S. (2004). A study of the index–futures price relationship within the Malaysian stock index futures market**.** *Derivatives Use, Trading & Regulation Volume*, 156-181.

Tse, Y. M. (1999). Price discovery and volatility spillovers in the DJIA index and futures markets. *The Journal of Futures Markets,* 911-930.

Yang, J., Yang, Z., & Zhou, Y. (2012). Intraday price discovery and volatility transmission in stock index and stock index futures markets: Evidence from China. *Journal of Futures Markets*, 32(2), 99-121.

Zhang Y. & Tong S.Y. (2009). Hong Kong's economy in the financial crisis. Retrieved from http://www.eai.nus.edu.sg/BB448.pdf.

Zhong, M. S., Darrat, A. F. & Otero, R. (2003). Price discovery and volatility spillovers in index futures markets-some evidence from Mexico. *Journal of Banking and Finance*, 3037-3054.